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SIMULATION ANALYSIS OF AN OUTPATIENT DEPARTMENT OF INTERNAL MEDICINE IN A UNIVERSITY HOSPITAL

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ABSTRACT

Soaring health care costs and greater emphasis on preventative medicine have compelled researchers to examine new ways to reduce costs and improve efficiency in outpatient services. Extended waiting times for treatment in the outpatient department followed by short consultations has long been a complaint of patients. This issue is becoming increasingly important in Japan with its progressively aging society. In this context, a discrete event simulation model was developed to examine doctor schedule mixes (DSMs) and various appointment schedules (ASs) in a mixed-patient type environment in an outpatient department of internal medicine of a university hospital. It could identify some of the best DSMs by integrating a simulation model into an optimization program. Combining one DSM found via an optimization program with some ASs, the patient waiting time could be reduced drastically without adding extra resources.

1 INTRODUCTION

Waiting time in outpatient departments is a problem throughout the world. One consistent feature of patient dissatisfaction has been expressed with the length of waiting time in the outpatient department. The waiting time is particularly important for a hospital, since the “customers’ are ‘patients”. Long waits create customer dissatisfaction on one hand and resources inefficiencies on the other hand. In Japan, with a progressively aging society, this has become a central issue in the healthcare industry.

Soaring health care costs and greater emphasis on preventative medicine have compelled researchers to examine new ways to reduce costs and improve the efficiency in outpatient services. In recent years, with a considerable increase in the movement of health care from in-patient cases to outpatient cases, outpatient services have gradually become an essential component in health care. In general many outpatient departments throughout the world have long waiting times for treatment followed by short consultations and together these have been a major complaint of patients. Over the years, this disproportionately long waiting time in the consultation room has been the focus of research among academicians and practitioners. Most researchers have stressed that the major reason for long waiting times is the poor scheduling system put in place.

However, though this subject has been researched for more than fifty years, a big gap exists between theory and practice. The major reason for this phenomenon is the unrealistic assumptions made in the model development process.

Nearly all published work has at least one of the following assumptions invalid to the actual context. Most of the studies considered a single-stage system so that other interrelated servers such as x-ray, receptionist, cashier, and lab test were ignored. Second, most of studies assumed that there was no secondary consultation for the patients going for lab tests and x-ray. Third, many studies have modeled the problem as a single-server system assuming only one doctor was available for consultation. Different types of patients, who were classified according to nature of their disease, visited the outpatient department so that a multi server system was the common feature in most outpatient departments. Fourth, most past studies focused on the patients who made appointments and ignored the walk-ins. Walk-ins are unavoidable in a hospital and their service time directly affects the waiting time of subsequent appointment patients. Fifth, there was no evidence in past research that there was use of actual service time instead of taking estimated sample data. Human interactions, such as patient-doctor relationship was unpredictable, so that the accuracy of estimated service time was debatable. Six, almost all studies have not taken into account that the other patients of the hospital utilized facilities that were also used by outpatients. An outpatient department is only one sub-system of the total hospital system hence inter-departmental dependency should not be overlooked. The present study formulates a multi-stage, multi-server and multi-customer model by relaxing these unrealistic assumptions.

There are two scheduling systems in outpatient departments: the patient and staff. Appointment scheduling and staff scheduling are the two aspects that determine the waiting time in the outpatient departments. These schedules should be organized according to the types of patients and consultation categories. As analytical techniques are unable to formulate the complexities of the outpatient department, this study uses the discrete event simulation methodology.

This study focuses on both aspects of the scheduling in a mixed-patient outpatient department at the Nagoya University hospital located at Aichi prefecture, Japan.

The objective of this study is to identify a schedule option by integrating a DSM with an AS which can help to reduce the waiting time at consultation rooms.

2 BRIEF LITERATURE REVIEW

In comparing the two scheduling methods, that is staff and patient, most of the research has been directed on the latter in outpatient departments.

In the case of patient scheduling, the types of appointment systems range from single-block appointments on the one extreme to individual appointments on the other. Most of the appointment systems have concentrated on modifying and combining these two systems into different forms. Any combination in the appointment interval, block size, and initial block create an AS rule.

The *single-block* system assigns all patients to arrive in a block at the beginning of the clinic session, allocating a "date" rather than a specific appointment time (Babes and Sarma 1991). Such a system was used in the past by most hospitals. The single-block system creates long waiting time for patients but shortens idle time for doctors.

The *individual-block/fixed-interval* system gives unique appointment times for patients staggered evenly over the clinical session (Klassen and Rohleder 1996).

Th*e individual-block/fixed-interval with an initial block* system is similar, but the number of patients assigned to the initial block is greater than one. Bailey (1952) introduced this rule to the AS literature, and Ho and Lau (1992) added some amendments.

Following an analytical approach, Soriano (1966) advocated the *multiple-block/fixed-interval* rule to the AS literature recommending patients be schedule two at a time with an interval of twice the consultation time.

Cox, Birchall, and Wong (1985) investigated the *multiple-block/fixed-interval with an initial block* rule, introducing an initial block to the above rule.

The *Variable-block/fixed-interval* assigns a different number of patients during the clinical session (Rising, Baron, and Averill 1973).

The *Individual-block/variable-interval* rule calls patients individually with unequal appointment intervals. Introducing this rule to the literature, Ho and Lau (1992) concluded that a variable-interval appointment-scheduling system designed to reduce patient waiting time performs well in most environmental conditions. A modified *Variable-block/fixed-interval* rule was modeled by Wijewickrama and Takakuwa (2005).

In addition to patient scheduling, a number of studies have addressed the problem from the point of staff scheduling. From this aspect, the staff is scheduled to meet patient demand while setting patient arrival as unchanged. Alessandra et al. (1978) studied both staffing levels and patient arrivals to identify the bottleneck and improve patient throughput. The scholars in this study proposed to distribute current morning appointment patients to the afternoon shift. Draeger (1992) identified an alternative which reduced average patient waiting time and average patient time in a system simulating nurse workload in an emergency department. Kumar and Kapur (1989) examined ten nurse-scheduling alternatives and identified the alternative that yielded the highest nurse utilization. Tan, Gubaras, and Phojanamongkolkij (2002) suggested the addition of one or two extra doctors for each hour in order to reduce the bottleneck at doctor stations. Centeno et al. (2003) developed a tool that integrated a simulation model and an integer linear program (ILP) to establish the staffing requirements for each period in an emergency department. The simulation model established the staffing requirement for each period, and the ILP produced an optimum calendar schedule for the staff.

3 MODEL

3.1 Description of the Outpatient Department

The outpatient department in this study operates from 8:30 am to 5.30 pm during weekdays with three different types of patient visits: appointment patients, same day appointment patients, and new patients. Like many outpatient departments in Japanese hospitals, the largest percentage (i.e., 86%) consists of patients with appointments.

Appointment patients have to go to the reception machine to show their attendance, while same day appointment patients have to go to the reception desk to get an appointment time. New patients have to go to the new patient desk for filling-out applications, showing their health insurance certificate and obtaining a patient's registration ticket. Patients who make a prior appointment have priority over other patients. Patients who make same day appointments have priority over new patients for a consultation.

There are ten types of patient categories which are based on required consultation service. They are blood, diabetes, kidney, senility, homebound, nerves, respiratory, digestive, circulatory and general. During the consultation with the doctor he decides whether the patient needs to be sent tests: blood, urinary, X-ray or endoscope tests or sent to the treatment room. Patients who undergo a test or treatment, have to consult the same doctor before leaving the hospital. After the second assessment, patients can leave the hospital. Patients can order needed drugs from a pharmacy by faxing in the prescription after settling the bill at the cashier. Although this is a generalized patient flow of the department there are more steps behind each of these activities which have to be addressed by the simulation model.

3.2 Performance Measures

The primary performance measures considered under this study were the patient waiting time for each of the types of patient.

In addition to this, to represent a single performance measurement for all types of patients together, an index-weighted average patient waiting time (WAPWT), was calculated using the following formula:

$$WAPWT = \frac{(APWTA * NA) + (APWTS * NS) + (APWTN * NN)}{NA + NS + NN}$$

where APWTA = Average patient waiting time for appointment patients; APWTS = Average patient waiting time for same day appointment patients; APWTN = Average patient waiting time for new patients; NA = Number of appointment patients; NS = Number of same day appointment patients; NN = Number of new patients.

3.3 Data and Simulation Model

The principal data source of this study was the electronic database from the clinical records. This Access database consisted of the patient appointment time, patient log-on and log-off time of the consultation service, patient type, patient category based on the required consultation service, and treatment time of the treatment service, if any. The arrival, payment and medical test data were stored in separate spreadsheet files. The other data was collected via interviewing administrators, doctors, nurses, and other clerical personnel, and by observation.

As shown in Figure 1, the Access query facility, patient records for each individual patient were retrieved and stored in another database. Secondly, as there were a number of sequence patterns, each sequence was identified using a VBA program written in Excel. This data is read by a special purpose data generator written in Excel VBA to generate experimental data to the Arena simulation model. The required input parameters are the incremental rate of total number of patients and patients' mix, and these parameters can be changed by the user in the beginning of the simulation run.

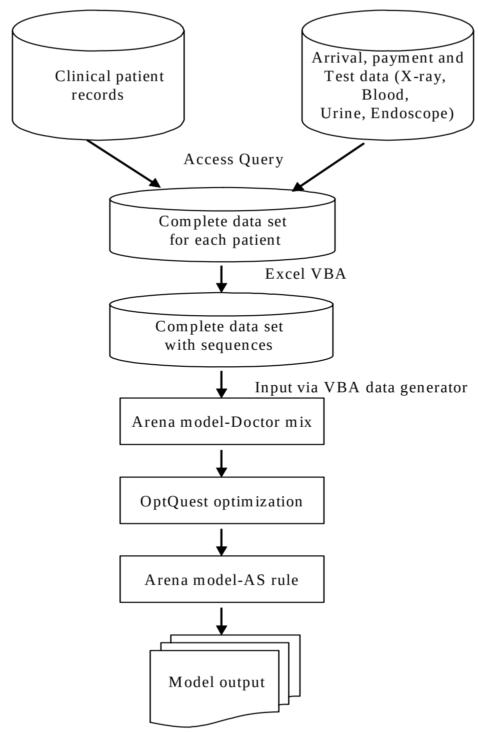

Figure 1: System integration

This kind of data generator has been used previously in three simulation studies in the health care field. The first study involved examining patients flows in an emergency department of a general hospital (Takakuwa and Shiozaki 2004). The other two studies examined the congestions of consultation rooms in outpatient departments of internal medicine (Wijewickrama and Takakuwa 2005, Wijewickrama 2006).

Using these two parameters (i.e., the incremental rate of total number of patients and patients' mix), the corresponding patient records were created for a given day. Table 1 shows a sample output created by the proposed data generator. By making use of this generated data as an external file input for the Arena simulation model, experiments can be conducted under any specified condition.

Next, the performance measures generated by simulation model were used by the OptQuest optimization program to search for an optimum DSM. Finally, AS rules were run based on DSMs found in the previous step.

This study used actual data such as consultation and arrival time rather than the application of estimated sample data. It is not necessary to argue that the results generated in considering such real data are more accurate and reliable. The other processing times were calculated by incorporating samples collected fitting to a probability distribution of the Arena input analyzer. Resources such as the

Table 1: Output of the data generator

Arrival time	Patient type	Sequence	Category	1st Consult time(min)	2nd Consult time(min)
7.83	1	114	7	9.18	3.83
7.83	1	114	2	3.80	3.30
7.84	2	116	2	11.93	11.46
7.84	1	160	3	8.68	16.80
7.84	1	160	4	4.21	9.35
7.84	1	160	1	15.00	6.60
7.84	1	14	3	10.56	
		Omitted			
8.03	1	16	7	2.51	

staff and medical facilities are summarized in Table 2 with the corresponding processing times.

The total number of visits was about 525 patients per day. There were thirty-one doctors employed on a given day. The list of the doctors who engaged in each service is shown in the Table 3. The working time of each doctor is based on schedules, including breaks.

A simulation model for the outpatient department was created using the simulation package Arena (Kelton, et al. 2004). The drawing was made to scale and considered all features pertinent to the study.

Table 2: Process and delay time of services (except consultation time)

Process	Time	Number
New patient reception (seconds)		
Document submission	8+WEIB (45.2, 1.37)	3
Office work 1	20+GAMM (61.6, 1.34)	3
Office work 2	TRIA (26, 53.9, 92)	1
Card issue	1+LOGN (12.4, 15.3)	1
Other patients reception (minutes)		
Appointment	0.25	2
Same day appointment	10	1
Blood test (minutes)	0.07+LOGN(1.85,0.951)	5
Treatment room (minutes)	LOGN (5.19, 13.9)	1
Urine test (minutes)	1	3
Endoscope test (minutes)	2.03+ERLA (1.29, 2)	3
X-ray (minutes)	1+7.9*BETA (1.08, 1.87)	5
Payment process (seconds)		
Accounting window	4+LOGN (19.4, 14.4)	3
Accounting process	NORM (20.7, 8.71)	4
Payment machine	19+GAMM (5.87, 3.39)	5

Table 3: Doctor mix

Consultation Service	No. of Doctors
Blood	3
Diabetes	5
Kidney	2
Senility	2
Homebound	1
Nerves	3
Respiratory	3
Digestive	5
Circulatory	5
General	2

3.4 Verification and Validation of the model

The model validation was the lengthiest step of the actual simulation model. This step in the project usually causes the most headaches in a health care simulation. A number of techniques were used to verify and validate the model.

First, an animation screen together with dynamic statistics and graphs provided a general view of the system behavior. For verification, the researchers closely examined whether the animation imitates the actual system. Second, in the case of face validity, a team evaluated the system and their valuable comments helped to augment the model. Third, the varying behavior of some performance measures were examined by adjusting the patient arrivals with incremental percentages. In addition to the above techniques, the execution of tracing, self-documentation, and checking the computerized representation by another developer were also used to build a more realistic model.

Based upon the results from the verification and validation techniques applied in the testing, the model provided realistic predictions for the system behavior under the various experimentations. This is explained in the next part of this paper.

4 EXPERIMENTATION

Results from the simulation model revealed that patients had to wait a long time to consult a doctor even though it may have taken only a few minutes to examine a patient. Considering appointed patients, for example, if the total time in the system from arrival to departure had a value of 100, then 70 percent was recorded as waiting time only for consultations. This figure is worse for the other two types of patients. Consequently, as in Figure 2, except for the blood service consultation, the highest waiting times (excluding the process time) were recorded in the consultation rooms.

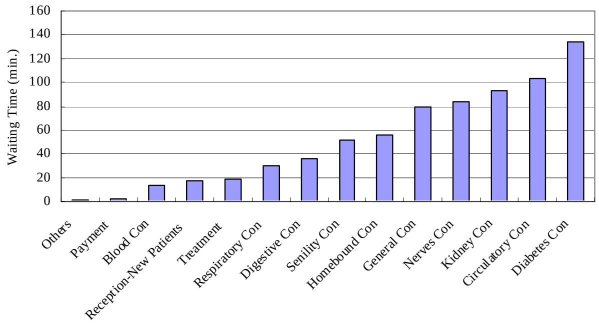

Figure 2: Break down of waiting time

As shown in Figure 3, the total number of patients waiting in front of the consultation rooms gradually increased to seventeen patients around 9 am, and the congestion decreased gradually until 2 pm.

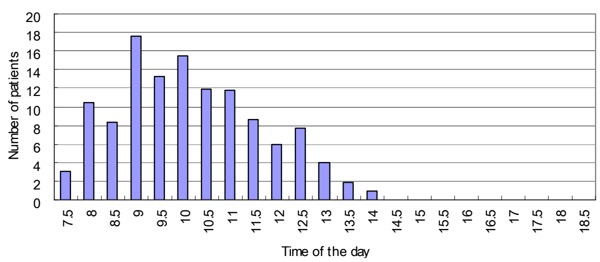

Figure 3: Waiting patient in time of the day

The experimental process concentrated on the issues of excessive waiting time at the consultation room, aiming to shorten the patients' waiting time or throughput time.

4.1 Evaluation of DSM

Figure 4 analyzes the proportion of total waiting time belonging to each patient category with the total number of waiting patients in each category. Interestingly, more than 45% of the total waiting time was spent by patients being treated for diabetes. This value for circulatory patients was 25%. Thus these two categories account for 70% of the total waiting time.

To investigate this issue further, it was necessary to analyze the behavior of waiting time for each consultation category in relation to each patient type. As Figure 5 shows, the waiting time was spread unevenly not only among consultation services, but also by patient type. This highlights the requirement of rearrange the existing DSM in order to provide a fair service for all types of patients.

Prior to applying an AS rule, this study combined the simulation model with a deterministic operational research technique to reach to an optimum solution. In order to reduce the long waiting time of the department we suggest an optimum DSM using an optimization program in Arena, called OptQuest. Glover et al. (1999) highlighted the value of this optimization program over a simulation as follows: "In spite of its acknowledged benefits, however, simulation has suffered a limitation that has prevented it from uncovering the best decisions in critical practical settings. As a consequence, the decision making goal of identifying and evaluating the best (or near best) options has been impossible to achieve in many applications" (p.255).

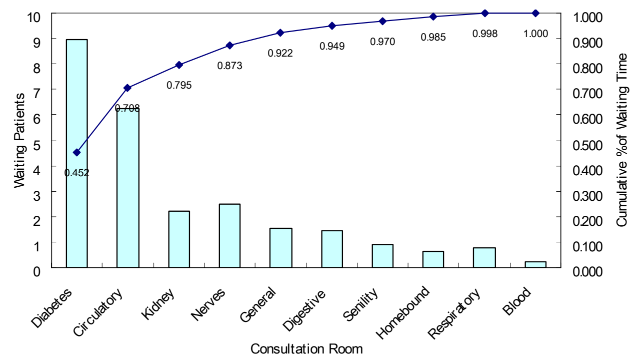

Figure 4: Proportion of total waiting time and waiting patients for each patient category

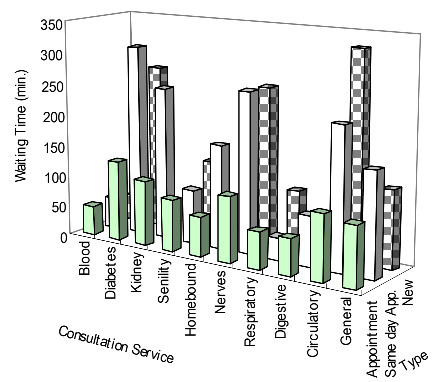

Figure 5: Waiting time for each consultation category with each patient type

A simulation can only provide estimates of performance measures and it is not an optimization tool. Hence, this section combines these two techniques to find the best DSM. OptQuest is an optimization program in Arena that uses a special search algorithm to search for the best solution or a near best solution. It uses heuristics known as *tabu* search and scatter to find the best value for one or multiple objective functions.

The objective of the optimization program is to minimize the weighted average patient waiting time (WAPWT) for consultation services. The total number of doctors was thirty-one and a minimum of one doctor was required for each consultation service. The model is as follows:

Minimize $Z = WAPWT$
Subject to following constraints

$$X_1 + X_2 + X_3 + X_4 + X_5 + X_6 + X_7 + X_8 + X_9 + X_{10} \le 31$$
$$X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10} \ge 1$$

Where
X_i = Number of doctors allocated for *i*th consultation service

One major advantage with integrating the simulation model with an optimization program is that the decision variables of the objective functions are not necessarily in the constraints. The following figure shows the graph of the above model when the time lapsed after 5 hours.

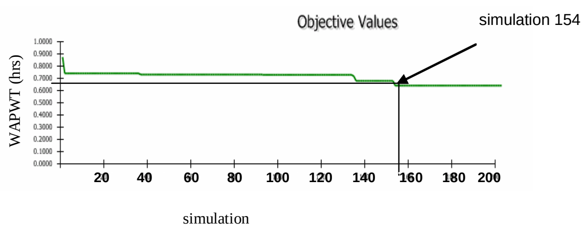

Figure 6: Performance graph

This graph shows the best result found so far as a function of the simulation number run. Within this time period, OptQuest evaluated 203 different scenarios, and the best one was discovered by the 154th scenario, where the total WAPWT was 38.466 minutes (0.6411 hours) for a single day, which was achieved with 31 doctors. A myriad of DSMs were identified which reduced the WAPWT compared to the base case. Table 4 shows a few of these mixes.

Table 4: Optimization results

Simulation	WAPWT	Doctor Mix										Total
	(min.)	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	Doctors
154	38.47	1	6	7	4	2	1	2	3	3	2	31
185	39.25	2	6	6	4	2	1	2	3	3	2	31
179	42.14	1	6	6	4	2	1	2	3	3	2	30
191	42.20	2	6	6	4	2	1	2	3	2	2	30
173	44.82	1	6	6	4	2	1	2	3	2	2	29
Base	51.92	3	5	5	5	2	1	2	3	3	2	31

Note:X1=Blood,X2=Circulatory,X3=Diabetes,X4=Digestive, X5=General, X6=Homebound,X7=Kidney, X8=Nerves, X9=Respiratory, X10=Senility

The optimum solution (i.e., simulation 154) improved the average waiting time by 26%, which represented a reduction of 117 hours waiting time per day compared to the existing system. Interestingly, reducing the total number of doctors by 2 (simulation 173) and by 1 (simulation 179) also improved the solution by 14% and 19% drop in patient waiting time respectively. In other words, in considering simulation 173, 61 hours of waiting time was saved by employing 29 doctors per day; which was a large reduction of idle time of both patients and doctors.

4.2 Evaluation of AS Rules

In this next step, we evaluated ten AS rules. These rules are summarized in Figure 7.

AS rule 1 calls a patient individually based on the average consultation time. The first set of appointment time in the day is zero ($A_1 = 0$) and the other times are at A_i th time. In schedule 2, two patients are appointed at a time with an interval of twice the average consultation times. Schedule 3, an individual rule, sets *k* to 0.01 by delaying the arrival from the second patient to the rest of the patients. The fourth AS modifies the individual appointment system by setting the schedule time slightly early for patients after the first patient using *k*=0.1. Rules five and six change the individual system by requiring the second to (*K*-1)th patients to arrive earlier, but the (*K*+1) to the last patient to arrive later. The rule AS 7 calls two patients at the beginning and then individually in average consultation time. Rules eight and nine modifies the AS 7 assigning three and four patients at the beginning, respectively. The last rule, AS 10, calls patients individually, and it delays arrivals after the first patient, assigning two different *k* times. In the first instance, the delayed time k_1 was assigned to *B*, or the number of patients called individually (in this case 5),and in the second delayed k_2 was assigned to *B*. This procedure continues alternatively until the last appointed patient.

AS 1.	$A_1 = 0;\ A_i = A_{i-1} + \mu_t,\ i > 1$
AS 2.	$A_i = A_{i+1} = (i-1)\mu_t,\ i = 1, 3, 5, \ldots.$
AS 3.	$A_1 = 0,\ k = 0.01;\ A_i = A_{i-1} + \mu_t + k\sigma_t,\ i > 1$
AS 4.	$A_1 = 0,\ k = 0.1;\ A_i = A_{i-1} + \mu_t - k\sigma_t,\ i > 1$
AS 5.	$k_1 = 0.25,\ k_2 = 0.5,\ K = 5;\ A_i = A_i - k_1 (K-i)\sigma_t,\ i \le K,$ $A_i - k_2 (K-i)\sigma_t,\ i > K$
AS 6.	$k_1 = 0.15,\ k_2 = 0.3,\ K = 5;\ A_i = A_i - k_1 (K-i)\sigma_t,\ i \le K,$ $A_i - k_2 (K-i)\ \sigma_t,\ I > K$
AS 7.	$A_1 = A_2 = 0;\ A_i = A_{i-1} + \mu_t,\ i > 2$
AS 8.	$A_1 = A_2 = A_3 = 0;\ A_i = A_{i-1} + \mu_t,\ i > 3$
AS 9.	$A_1 = A_2 = A_3 = A_4 = 0;\ A_i = A_{i-1} + \mu_t,\ i > 4$
AS 10.	$k_1 = 0.1,\ k_2 = 0.5,\ B = 5,\ A_1 = 0;$ $A_i = A_{i-1} + \mu_t + k_1\sigma_t,\ i > 1 \ldots.(1)$ $A_i = A_{i-1} + \mu_t + k_2\sigma_t. \ldots.(2)$

μ_t : Average Consultation Time, σ_t : Standard Deviation of Consultation Time

Figure 7: Appointment schedules

The experimental results of the AS rules on WAPWT are tabulated in Table 5. Interestingly, almost all ASs have reduced the WAPWT compared to the base case. More specifically, the AS 10, a *modified Variable-block/fixed-interval* rule, reduced the waiting time by 59.65% on the WAPWT against the base case. Generally, the *variable-*

interval rules (ASs 10 and 5) outperform all cases except for the AS 3. Conversely, some well-known AS rules such as the two-at-a-time (AS 2), Baily's rule (AS 7), and modified Baily rules (ASs 8 and 9) were underperformed in the actual context.

Table 5: Waiting time for each AS rules

AS Rule	**WAPWT(Min)**	**% of Reduction**
1	35.98	30.70
2	37.11	28.52
3	24.4	53.00
4	44.91	13.50
5	29.44	43.30
6	32.09	38.19
7	39.69	23.56
8	46.32	10.79
9	51.77	0.29
10	20.95	59.65
Base	51.92	0.00

4.3 Combining AS Rules with a DSM

For the purpose of further reducing the waiting time, each AS was applied in some of the best DSMs identified in the optimization program. After running a number of alternatives, it was revealed that the DSM identified as "simulation 185" of the Table 4 was the best. Applying this mix for each ASs, the following results were obtained.

Table 6: Waiting time for each AS rules on "simulation 185"

AS Rule	**WAPWT(Min)**
1	35.052
2	36.69
3	23.94
4	42.918
5	29.322
6	31.614
7	38.562
8	46.512
9	51.912
10	20.796

The results show that except for eight and nine, all rules could reduce the waiting time without adding a resource. Moreover, combining AS 10 to the DSM identified as "simulation 185", the *cumulative percentage of waiting time* line has been closed to the diagonal of the graph in Figure 8. Seeing this it is clear, that all types of patients experience a somewhat similar waiting time in proportion to the existing system.

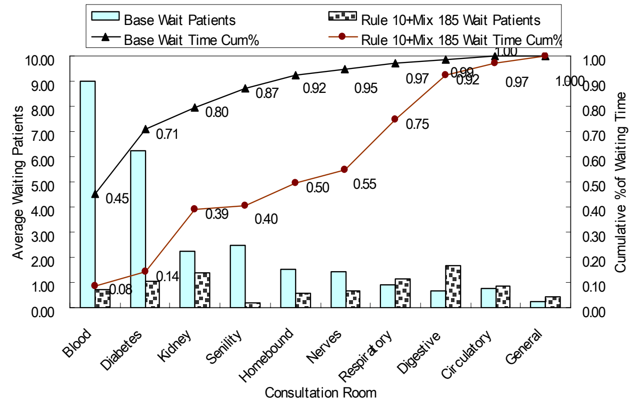

Figure 8: Proportion of total waiting time and waiting patients for each patient category for base vs. optimum solution

Based on AS 10, the percentage of reduction of the WAPWT was 59.95%. In other words, 31 minutes were saved for one patient. This corresponds to 272 total hours per day.

5 CONCLUSIONS

A simulation analysis was made on the outpatients department of a university hospital in Japan. Results show that under the existing system, patients have to wait for a long time for consultations that only last for a few minutes. The experimentation processes concentrated on this issue aiming to shorten the waiting time by identifying an optimum schedule in terms of both patients and doctors.

First, the impact on WAPWT was analyzed identifying an optimum DSM using an optimization program. The program identified an optimum scenario which could reduce the average waiting time by 26%. This identified another scenario which could save 61 hours in terms patient waiting time per day by employing 29 doctors instead of 31 doctors of the existing system.

Second, among the ten AS rules, one *modified individual-block/variable-interval* rule was able to reduce the WAPWT by 59% compared to the existing system.

Finally, applying some ASs to one best DSM, it could reduce patient waiting time further, without adding a single resource.

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